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MODELS OF THE LEARNER IN COMPUTER-ASSISTED INSTRUCTION

J. D. Fletcher

Navy Personnel Research and Development Center
San Diego, California

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J. D. Fletcher

Reviewed by
J. D. Ford, Jr.

Approved by
J. J. Regan
Technical Director

Navy Personnel Research and Development Center
San Diego, California 92152

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The adaptability of computer-assisted instruction to individuals should be enhanced by the use of explicit models of the learner. To be appropriate for computer representation, these models must take the form of effective procedures. Such procedures may be derived from four areas of investigation: quantitative models of memory, regression models of performance, automaton models of performance, and artificial intelligence. Relevant work in these four areas is identified and reviewed.

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FOREWORD

This report is the first in a series documenting work completed under Technical Development Plan ZPN07 (Education and Training Development), Work Unit ZPN07.P32 (Advanced Computer-Based System for Instructional Dialogues). This work unit will test and evaluate techniques for computer generated instruction. This type of instruction can be distinguished from more conventional approaches by the automation of instructional interaction and choice of strategy. This approach promises to reduce the costs of instructional materials preparation and to increase the adaptability and individualization of the instruction delivered. One aspect of this approach is the representation, by computer, of learner capabilities and needs. This report identifies and reviews relevant learner representation techniques that are reasonable candidates for tryout in Navy training environments.

The author acknowledges the continued support and encouragement of Dr. J. D. Ford, Jr., Program Director for the Development of Training Technology.

J. J. CLARKIN
Commanding Officer

SUMMARY

Problem

The central problem in computer-assisted instruction is the translation of instructional practice, which is fairly vague, into computer programs, which are quite precise. If effective procedures are isomorphic with computer programs, this problem is one of translating instructional practice into effective procedures. Models of the learner may be essential in translating instruction into effective procedures.

Purpose and Approach

This report reviews the explicit use of models of the learner based on quantitative models of memory, regression models of performance, automaton models of performance, and artificial intelligence.

Findings

Models of Memory. Four quantitative models of memory have been investigated for their utility in modeling learners in computer-assisted instruction: the incremental model, the one-element model, the random-trial increments model, and models based on General Forgetting Theory. Instructional strategies based on the incremental model are termed response insensitive because they concern the number rather than the outcomes of presentations. Strategies based on the one-element model, the random-trial increments model, and a General Forgetting Theory are termed response sensitive because they take into account the outcomes of presentations. General Forgetting Theory meets a need for a time-dependent forgetting process in modeling learners' knowledge of items. However, only locally optimal instructional strategies have been derived from General Forgetting Theory. Global optimization strategies that maximize gain over the entire instructional treatment have been derived from the incremental, one-element, and random-trial increments models.

Regression Models. Despite considerable use of regression models to describe student progress in computer-assisted instruction, only two examples of these models used to dynamically predict and prescribe instruction for individual students were found. Predictive control based on regression models of performance using such independent variables as percent correct, response latency, and measures of state and trait anxiety has been used successfully to teach concepts associated with heart disease. A theory of student progress derived from a stochastic differential equation may be applicable to a variety of curriculums and has provided very precise predictive control in experiments on computer-assisted instruction in arithmetic computation. Although regression models are well understood and easy to apply and modify, they are sufficiently powerful to satisfy many more applications than

have yet been attempted. Through the use of regression models, computer-assisted instruction, which can dynamically adjust to within-course performance as well as entering course measures, may realize the intuitive promise of aptitude-treatment interaction.

Automaton Models. What computers do and what effective procedures are may be most easily described in terms of automata theory, and it is reasonable to turn to automata theory for models of the learner that may be easily represented by computer and used in computer-assisted instruction. The power of automaton models can be seen in contrast with models based on regression. However, regression models are applied to grouped data. No matter how adequate they are for many applications or how accurately they predict performance, they do not postulate the specific algorithmic processes that students use in solving problems. On the other hand, analysis of these algorithms is a natural, integral aspect of automaton models. Use of these models is just beginning, but they have already demonstrated their utility in describing the algorithmic processes used by students in solving arithmetic problems.

Models as Artificial Intelligence. Several computer-assisted instruction projects have been based on models of such formally structured subject matter as mathematical logic, electronic troubleshooting, and computer programming. Additional efforts are being made to extend this approach to less formal subject matter such as South American geography and history of the American Civil War. All these efforts attempt to devise adequate models of the learner by starting with an adequate model of some subject matter and "shading it in" as the learner masters given aspects of it. Another approach is to model human belief systems directly. This latter approach has not been applied to computer-assisted instruction, but fairly adequate models of belief systems have been devised for several levels of paranoia and for a "Cold Warrior." Given all that must be represented as discrete facts and all the interrelations between these facts, adequate representation of a human belief system may be unattainable. However, a belief system for an instructional subject may be simpler and more amenable to computer representation.

Conclusion

Implicit in the review is the assumption that explicit representations of the learner should be applied in computer-assisted instruction. Instruction does not merely deposit information on blank slates. Students comprise complex, dynamic systems that are altered by instruction. The more precisely these student/systems are explicated, the better instruction can be devised, modified, evaluated, and individualized. Moreover, the approaches to instruction discussed by the review use to advantage the power, speed, and accuracy of computers, and, in doing so, illustrate unique and valuable capabilities of computers applied to instruction.

CONTENTS

INTRODUCTION

Problem

The central problem in computer-assisted instruction (CAI) is the translation of instructional practice, which is fairly vague, to computer programs, which are quite precise. If effective procedures are isomorphic with computer programs, this problem is one of translating instructional practice into effective procedures. Turing (1936) argued that any procedure programmed for a computer is computable and effective, and he did not, current apocrypha to the contrary, argue the converse of this statement. However, in agreement with Minsky (1967) and others, this report assumes that any procedure that is effective can be programmed for a computer.

Models of the learner may be essential in translating instruction to effective procedures. In a sense, all CAI includes these models either implicitly or explicitly. In a linear sequence of curriculum items, a student is modeled by that sequence and by his position in it. In a non-linear, branching sequence, a student is modeled by the branching structure and, again, by his position in it. This suggests that content analysis of curriculum and models of the learner are dependent and inextricable, but this suggestion will not be argued here.

Purpose and Approach

This report reviews the explicit use of models of the learner based on quantitative models of memory, regression models of performance, automaton models of performance, and artificial intelligence.

RESULTS AND DISCUSSION

It is obviously beyond the scope of this paper to present a comprehensive analysis of the use of models in psychology. It should be sufficient to say that the use of models has been an integral aspect of psychology for a long time. The use of quantitative, or "mathematical," models, which lead directly to effective procedures, has occurred more recently. Beginning with the search for a universal, analytic learning function by Robertson, Thurstone, Woodrow, and others, it is possible to trace a gradually increasing emphasis on systematic specification of the elementary units underlying learning. Hull's Principles of Behavior (1943) is a landmark in this regard. Hull's postulates, which were designed to encompass the major aspects of learning, initiated considerable empirical research. However, it is not possible to make more than a few quantitative predictions of behavior from these postulates. Be that as it may, the work of Hull, Lewin, Tolman, and others emphasized the importance of quantitative theory in psychology and set the stage for the more recent work of Atkinson, Estes, Luce, Suppes, and many others.

Considering the current status of quantitative models, there appears to be a trade-off between the precision and the breadth and/or complexity of the phenomena they account for. This report discusses models of the learner in order of increasing complexity, moving from quantitative models applied in simple learning situations to more qualitative models applied in more complex situations.

Models of Memory

Although earlier work can be cited (e.g., Karush and Dear, 1966; Matheson, 1964), a 1966 paper by Groen and Atkinson appears to have been seminal in the application of models of memory to instruction. Groen and Atkinson tied the application of quantitative learning models to the optimization of instruction. The prototypal instructional situation addressed by this and similar papers was first presented by Suppes' (1964) analysis of learning a list of items. Roughly, a set of M items is to be learned in a fixed number, S, of sessions. On each session a subset of the M items is presented for study. The optimization problem is to maximize performance on a posttest of all M items by appropriate selection--in size and/or content--of the subsets subject to the constraints presented by M and S. This optimization problem is generally solved by the particular model of memory chosen to represent the learner, and discussions of optimized instruction would be academic were it not for the use of computers in instruction. These discussions typically start with the single-operator, or incremental, model (Bush and Sternberg, 1959) and the all-or-none, or one-element model (Estes, 1960). These two models have become prototypal and serve as standard straw-men in the development of learning models.

The incremental model assumes that the probability of an error on item i on the n+1 presentation ($q_{i,n+1}$) is

$$q_{i,n+1} = aq_{i,n} \quad \text{where } 0 < a < 1.$$

In other words, the probability of an error on an item is reduced by a constant amount every time the item is presented, no matter what happens on the presentation. The magnitude of the constant amount is estimated by a parameter, a, that is uniquely determined for each learner.

The one-element model assumes that, for each student, each item to be presented is in one of two states--learned or unlearned. When an unlearned item is presented, it moves into the learned state with probability c. Specifically, the probability of an error on item i on the n+1 presentation ($q_{i,n+1}$) is

$$q_{i,n+1} = \begin{cases} q_{i,n} & \text{with probability } 1-c \\ 0 & \text{with probability } c. \end{cases}$$

In other words, the probability of an error on an item remains constant no matter how many times it is presented until a correct response to the item is made, at which time the probability of an error on the item immediately drops to zero and remains there forever. The probability of a correct response is estimated by a parameter, c, that is uniquely determined for each learner.

Given their simplicity, it is not surprising that these models have become straw-men or even whipping boys. What is surprising is the large amount of experimental data they account for. There are many experimental situations in which these models adequately describe the phenomena observed.

Both the incremental and the one-element models predict the same learning curve for a given set of items. As Calfee (1970) pointed out, they differ in their assumptions about underlying processes, and these differences hinge on the response-dependent character of the one-element model. The conditional probability of an error on presentation n+1 of item i, given an error on trial n, is

$$P(q_{i,n+1}|q_{i,n}) = a^n q_{i,1}$$

for the incremental model and

$$P(q_{i,n+1}|q_{i,n}) = (1-c)q_{i,1}$$

for the one-element model. Notably, the latter probability is not a function of trial number; learning either occurs or does not occur solely as a function of the parameter c in the one-element model. For this reason Groen and Atkinson termed instructional strategies based on the incremental model as response

insensitive because they concern the number rather than the outcomes of the presentations, and strategies based on the one-element model as response sensitive because they consider outcomes of item presentations.

Dear, Silberman, Estavan, and Atkinson (1967) reported the first application of a quantitative memory model to CAI. They used a presentation strategy based on the one-element model to teach paired-associates under computer control. Although their strategy was theoretically optimal, it required massed presentations and produced poor results relative to those obtained from a standard presentaton schedule that required distributed presentations. The point to be emphasized here is that a theoretically optimal procedure may not be the best instructional procedure available. An optimal procedure attempts to maximize some outcomes subject to some constraints. These outcomes and constraints may comprise a model of an instructional situation and, to the extent that this model is accurate, it will produce superior instructional outcomes. The Dear et al. study tested both the adequacy of an optimal procedure and its underlying instructional model; thus, it provided important feedback both to those concerned with instructional procedures and with theories of human learning. Greeno (1964) and Groen and Atkinson (1966) had suggested that the one-element model may fail badly in accounting for learning under massed presentation, and it was reasonable to avoid massed presentation in subsequent tests of the Dear et al. strategy.

Lorton (1973) compared a modified form of the Dear et al. strategy with a standard strategy based on the incremental model in presenting CAI in spelling to disadvantaged 4th through 6th grade students. Lorton's modification disallowed the presentation of any item more than once in any session. His results indicated a lesser error rate during training for the strategy based on the incremental model, but significantly better posttest performance for the strategy based on the one-element model. Using the modified Dear et al. strategy, then, Lorton demonstrated the anticipated superiority for a response sensitive, optimal strategy in a posttreatment measure of achievement.

Laubsch (1970) took a step further and applied a presentation strategy based on the random-trial increments model (Norman, 1964) to teach Swahili vocabulary to native speakers of English[1]. The random-trial increments model includes the features of both the incremental and one-element models by assuming that the probability of an error on item i on the n+1 presentation ($q_{i,n+1}$) is

$$q_{i,n+1} = \begin{cases} q_{i,n} & \text{with probability } 1-c \\ aq_{i,n} & \text{with probability } c. \end{cases}$$

It should be noted that, if $c < 1$, a strategy based on the random trial increments model will be response sensitive in that it will have to attend

[1]Although Lorton's study was documented after Laubsch's, it was designed and run earlier.

to the outcomes of prior presentations. Laubsch's study was motivated by the consideration that the assumptions of subject and item homogeneity in strategies based on the one-element model are untenable in most practical situations. The review by Atkinson and Paulson (1972) emphasized that an essential contribution of Laubsch's investigation was the development of a strategy based on the random-trial increments model to allow the parameters of the model to vary with different students and different items. Laubsch concluded that although significant improvements in learning can be achieved by applying optimal presentation strategies based on models of memory, these models are inadequate in an important aspect: they do not include a time-dependent forgetting process.

This inadequacy was directly addressed in a paper by Paulson (1973), who discussed the implications of the General Forgetting Theory formulated by Rumelhart (e.g., 1967) for presentation strategies based on different varieties of the one-element model. The General Forgetting Theory can be briefly described as assuming that a subject at any given time is in one of three possible states of learning with respect to any item: (1) an unlearned state (U), (2) a short-term retention state (S), or (3) a long-term retention state (L). As formulated by Paulson, when an item is presented, transitions between states occur according to the following stochastic matrix:

$$
\begin{array}{lc}
 & \text{State on trial } t+1 \\
 & \begin{array}{ccc} \quad L & \quad S & \quad U \end{array} \\
\begin{array}{r} L \\ \text{State on} \quad S \\ \text{trial } t \quad U \end{array} & \begin{bmatrix} 1 & 0 & 0 \\ c & 1-c & 0 \\ a & b & 1-a-b \end{bmatrix}
\end{array}
\qquad
\begin{array}{c}
\text{Probability of a correct} \\ \text{response given the state} \\
\begin{bmatrix} 1 \\ 1 \\ g \end{bmatrix}
\end{array}
$$

In other words, if an item is in the learned state, it stays there forever. If an item is in the short-term state and is presented, it may either change to the learned state or remain in the short-term state. If an item is in the unlearned state, it may change either to the learned or short-term state or it may remain in the unlearned state. The probability of a correct response to an item in the learned or short-term state is one, while the probability of a correct answer to an item in the unlearned state is equal to some guessing parameter.

Under the General Forgetting Theory, it is also necessary to consider items that are <u>not</u> presented on a trial. Transitions between states for these items occur according to the following matrix:

$$
\begin{array}{ccc}
 & & \text{State on trial } t+1 \\
 & & \begin{array}{ccc} L & \quad S \quad & U \end{array} \\
\begin{array}{r} \\ \text{State on} \\ \text{trial } t \end{array} & \begin{array}{c} L \\ S \\ U \end{array} & \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1-f & f \\ 0 & 0 & 1 \end{bmatrix}
\end{array}
$$

In other words, only items in the short-term state may change state during a trial in which they are not presented; they may either stay in the short-term state or drop back to the unlearned state. If we are willing to think of time measured by trials or presentations rather than minutes, these transitions answer Laubsch's call for a time-dependent forgetting process.

Despite the inclusion of a forgetting process, presentation strategies based on the family of models represented by the General Forgetting Theory incorporate a serious limitation. With respect to this limitation, two types of optimal strategies can be distinguished: (1) local strategies that maximize immediate gain, and (2) global strategies that maximize gain over the course of the instructional treatment. Paulson demonstrated that the difficulty in applying the General Forgetting Theory to the derivation of globally optimal strategies is that these strategies require looking more than one trial ahead in all cases of interest. The tractability of the one-element model in deriving a globally optimal strategy is a fortunate exception to a general rule of intractability. Paulson discussed several locally optimal strategies based on the General Forgetting Theory that look only one trial ahead. These strategies are mathematically manageable and intuitively reasonable, but they were all shown not to be globally optimal.

It is important to note that the application of quantitative models of memory is not a straightforward process of selecting the most adequate model available, grinding through the necessary mathematics to derive an optimal presentation strategy, and programming the strategy on the local CAI system. The verification task for selecting the most adequate available model is undecidable. The mathematics for demonstrating that a selected strategy is optimal may be prohibitively difficult. The selected strategy may not be implementable on a computer in general or on the particular operating system available. A global, quantitative theory for deciding these problems may someday be developed, but, in the interim, selection of optimal presentation strategies for CAI must necessarily depend on the biases of concerned individuals and on the results of empirical investigations.

The limitations of the learning situations to which these quantitative models can be applied were mentioned earlier. Considering these limitations, the number of remaining, unresolved issues is especially notable. It can hardly be overemphasized that we are just beginning to apply these models to instruction.

Regression Models of Performance

There has been considerable use of regression models to describe the progress of students in CAI (e.g., Searle, Lorton, and Suppes, 1973; Suppes, Fletcher, Zanotti, Lorton, and Searle, 1973). Such applications are analogous to the use of production functions in economic theory and can be used for both the optimization and the evaluation of instruction (Fletcher and Jamison, 1973). The use of regression models to predict and prescribe instruction dynamically for individual students has been less common. Two examples of this type of application are represented by the work of Rivers (1972) and Suppes, Fletcher, and Zanotti (1975a, 1975b).

Rivers documented an application of multiple linear regression to an elementary course in heart disease. He identified nine concepts taught in the course and, based on existing student performance, devised linear regression models for posttest performance on the concepts, given cummulative course performance up to and including the presentation of each concept. After adjustments, regression models that predicted posttest performance were devised for seven points in the program, i.e., after presentation of each of seven concepts. A student could be given remedial work after finishing a concept and before proceeding in the course if his posttest performance was predicted to be sufficiently low by the relevant regression model. These models included such independent variables as percentages of correct responses, response latency, and performance on state and trait anxiety scales.

Rivers compared the posttest performance of four treatment groups. The first group received remedial material as indicated by the regression models; the second received all prepared remedial material; the third received no remedial material; and the fourth received remediation at the option of individual students. There were no significant differences in posttest performance between the regression model group and the all-remediation group, but both these groups performed significantly better on the posttest than the no-remediation group and the student-choice group. Notably, the regression model group averaged less time in the course than the all-remediation group, but this difference was not significant.

Suppes, Fletcher, and Zanotti used regression models of achievement derived for individual students to determine unique goals for individual students and the amount of instructional intervention required by individual students to reach their goals. Suppes et al. (1975a) documented a theory of student progress from which was derived a stochastic differential equation that may be characteristic of many curriculums. At time zero, this equation takes the following simple form:

$$y(T) = a + b\,T^{c}$$

where y(T) represents the position of the student in the course (Suppes et al. take this postion to be grade placement measured by a standard, paper-and-pencil achievement test); T represents the amount of time measured by minutes or sessions a student may spend in the course; and a, b, and c are parameters of the model uniquely estimated for each student.

For achievement in arithmetic computation, Suppes et al. (1975a) reported a mean standard error of estimate of .06 in years of grade placement, with a range of .02 - .25, when c was set to a constant value for all students and only a and b were estimated for individuals. Notably, if c is constant, the equation is intrinsically linear in the sense of Draper and Smith (1966). If c is allowed to vary, the equation is no longer intrinsically linear, but it can be effectively estimated by the Golub-Pereyra algorithm (1972).

Obviously, there is room for more work in the application of regression models to achieve predictive-control in CAI. Although these models are well understood and easy to apply and modify, they are sufficiently powerful to satisfy many more applications than have yet been attempted. Although Rivers used both anxiety measures and within course measures, the number of personality and aptitude measures that might be entered into regression models of performance is large and worthy of investigation. Cronbach and Snow (1969) suggested that these entering measures may be insufficient for prescribing instructional intervention by themselves. However, in the context of CAI, which can dynamically adjust to within-course performance as well as entering course measures, the intuitive promise of aptitude-treatment interaction may be realized. The quantitative theory of curriculum progress presented by Suppes et al. was derived from qualitative principles. These principles and the theory presented are subject to empirical scrutiny. The strength of this theory is its generality; it can be directly applied to a wide variety of CAI in a straightforward manner with a minimum of empirical tinkering.

Automaton Models of Performance

What computers do and what effective procedures are may be most easily described in terms of automata theory (cf. Minsky, 1967; Moore, 1964). An automaton may be described as a device with a finite number of internal states which change in response to letters from a finite alphabet. These letters are presented one at a time on a tape which is "read" sequentially by the device. It seems reasonable to turn to automata theory for models of the learner that may be easily represented by computer and that may be used in CAI. Suppes (e.g., 1969) and Offir (1973) have discussed such applications in detail. An impetus for these applications is Suppes' (1969) demonstration of an asymptotic isomorphism between a given recognition automaton (Rabin, 1964) and a derivable stimulus-response model. In making this demonstration, Suppes identified internal states of automata with the responses of organisms. Different states of conditioning of the organisms were represented by different automata rather than by different internal states of automata. Sets of stimuli that might be presented to organisms were represented naturally and obviously by the letters of the finite alphabet recognized by the automata.

For behavioral data, it is intuitively desirable to introduce some stochastic notions into automaton models of organisms. Suppes (1969) did this by turning from deterministic automata to probabilistic automata in devising a model for column addition of integers in which the integers and their sums all have the same numbers of digits. The power of this approach can be seen in contrast with models based on regression. Regression models are applied to grouped data. Thus, no matter how adequate they are for many applications or how accurately they predict performance, they do not postulate the specific algorithmic processes that students use in solving problems. On the other hand, analysis of these algorithms is a natural, integral aspect of automaton models.

Offir (1973) presented another analysis of CAI performance data in elementary addition based on an application of stochastic sequential machines (Paz, 1971). The models developed by Offir are more elegant than the earlier models devised by Suppes in that the algorithmic processes are described more parsimoniously and are more powerful in that between--problem dependencies can be included. In applying these models to CAI performance data from two-integer vertical addition problems, Offir was also able to avoid two assumptions made by Suppes. These assumptions were that (1) if a carry error is executed, the probability of a correct response in that column is negligible, and (2) responses in different columns are independent.

Suppes and Flannery (in preparation, but see Suppes, 1974 or Fletcher and Suppes, 1975) used register machine models to compare the performances of deaf and hearing students on a variety of elementary arithmetic problems presented in CAI. The results of this study derived considerable value from the precision with which the arithmetic processes used by the learners could be modeled. On one hand, the study demonstrated with some certainty that objective features of the curriculum (for example, whether a vertical addition problem has a carry or not) were processed in much the same way by both deaf and hearing children. On the other hand, the study provided knowledge of the arithmetic processes used by the students that could have been used to individualize their instruction and, in so doing, would serve as precise models of the learners. In any case, CAI represents a serious hope for realizing the potential inherent in the dynamic, interactive application of these automaton models to instruction.

Models as Artificial Intelligence

A common complaint about quantitative models is that they are not "cognitive." This complaint may stem from the lack of complexity in the behavior the models account for, and/or from the lack of intuitive bases for the parameters of the models. In either case, it may be reasonable to turn to artificial intelligence for more satisfactory models of the learner.

Although they have not been addressed directly to CAI, the claims for artificial intelligence hold considerable promise. Newell and Simon (1972) have discussed methods such as generate and test, heuristic search, and matching

that may be prototypal in general problem solving. Newell, Shaw, and Simon (e.g., 1960) worked for several years on a general problem-solving computer program. Final' ·lson (e.g., 1968; 1973) and Colby (e.g., 1967; 1973) have developed c · programs to model human belief systems.

In discussing ,hilosophical problems of artificial intelligence, McCarthy and Hayes (1969 listinguished two aspects of intelligence—an epistemological part and a heuristic part. The epistemological part represents, or models, the world so that problem solutions follow from what is represented. The heuristic part actually solves the problem and decides courses of action. Most recent work in artificial intelligence has been concerned with the epistemological part of intelligence. Once "reality" is adequately represented, appropriate problems should be sufficiently well defined to facilitate derivation of effective procedures, or heuristics, for solving them. McCarthy and Hayes proceeded to distinguish metaphysically adequate representations from epistemologically adequate representations. A representation is metaphysically adequate if it does not contradict those aspects of reality that are of interest. It is epistemologically adequate if it does not contradict aspects of reality that are known. What computers cannot do may hinge on this distinction. For instance, Dreyfus' (1972) discussion of problems in artificial intelligence seems to hinge directly on the distinction of metaphysically adequate representations from epistemologically adequate representations. Dreyfus' point seems to be that there is no effective procedure for distinguishing what we need to know in some context from what we know. This point gains importance in considering artificial intelligence approaches to CAI.

Goldberg (1973) attempted to devise a metaphysically adequate representation by basing her approach to CAI on formally structured subject matter. Goldberg developed a proof-interpreter for CAI in mathematical logic. This interpreter imitated the adaptive behavior of a human tutor by supplying relevant hints to students and by encouraging students to use diverse solution paths. The interpreter was used in a CAI system that permitted a student to specify or extend the axiomatic theory he was studying. It should be emphasized that the hints and diverse solutions indicated by the program were devised dynamically and interpretively; they were not pre-specified or pre-stored. Goldberg's model of the learner, then, was basically a model of the subject matter that represented the learner by keeping track of the subject matter he had mastered. In another sense, however, Goldberg's proof-interpreter in its entirety modeled an ideal student-graduate of the course and represented the behavior that was the goal of the instruction. Notably, the proof-interpreter could not only complete the proofs required of students, but it could also take a student's own proof steps into account as it searched for a solution. In this sense, the proof-interpreter did not represent a single idealized student-graduate but, rather, the ideal to which a particular student might aspire.

The limitations of Goldberg's system appear to have been along the lines of epistemological and metaphysical adequacy discussed earlier.

> To what extent, then does the computer-based tutor fail to perform as well as a human teacher might? The answer to this question is based on the ability of the human teacher to leave the present domain of discourse and to borrow freely from general sources of knowledge. The human teacher can let the student ask general questions, and can devise illustrations from other subject areas in order to help the student understand the answer to his query. The human teacher is not as restricted, as is the present computer-tutor, in formulating the tutorial dialogue, or in allowing interruptions from the student which could be useful in inferring problems the student may be experiencing (p. 255).

The strengths of the system are powerful and obvious. It never errs, misleads, or ignores progress made by the student; it is infinitely patient; and it serves many students simultaneously.

Several other CAI projects have been based on metaphysically adequate models of formally structured subject matter. Brown, Burton, and Bell (1974) devised a computer representation of electronic equipment that both supported CAI and revealed operating characteristics of the equipment that had not been anticipated by the manufacturer. Barr, Beard, and Atkinson (1975) are attempting to develop CAI techniques to judge the semantic correctness of student-written computer programs based on a representation of the BASIC computer language. Finally, work reported by Collins, Warnock, and Passafiume (1974) supports mixed-initiative CAI based on a representation of South American geography. This type of CAI is called mixed-initiative because inquiries can be initiated by either the student or the computer. It is reasonable to expect increasing use of subject matter models in CAI. Clearly one way to devise adequate models of the learner is to start with an adequate model of the subject matter and "shade it in" as an individual masters given aspects of it. A useful review of some of this work was presented by Self (1974).

Another approach is to model human belief structures directly. Colby, at Stanford, and Abelson, at Yale, have been investigating computer simulations of human belief systems for several years. Colby's original intention was to simulate neurotic belief systems and the change they might undergo during psychotherapy (cf. Colby, 1967). This resembles what we would like to see in CAI. A belief system in both Colby's and Abelson's formulations is a set of interdependent concepts which could reflect the status of a student and the changes in his belief system or concept structure that might result from instructional intervention. Such a system could simulate the effects of instruction on a student so that the best instructional alternatives might be chosen for given objectives. As Colby has pointed out (1973), the difficulties of these tasks have limited him to the first, epistemological part--modeling the belief systems. Evidently, both Colby and Abelson have suspended

work on the heuristic part concerned with changes in the system. Applications of these models to CAI as, perhaps, criterion-referenced representations of the learner are still desirable and, based on the evidence, possible. Colby's success in modeling a paranoid belief system is attested by a verification experiment reported by Colby, Hilf, Weber, and Kraemer (1972). In a test based on Turing's (1950) suggestions, therapy protocols from computer models of strong and weak paranoia and from human patients exhibiting paranoia were compared by practicing psychiatrists. None of the psychiatrists were aware that a computer model of paranoia was involved. The psychiatrists rated the strong version of the computer model significantly higher in paranoia than the human patients, and the weak version of the computer model significantly lower in paranoia than the human patients.

Abelson (cf. 1973) has taken a more theoretical approach to the problem, basing his techniques on work in computer understanding of natural language concepts by Shank (e.g., 1972). This work holds great promise, both with respect to the espistemological and metaphysical adequacy of the representations it may produce and with respect to the heuristics for change that should result. Abelson's model of a human belief system, the Cold Warrior, has indicated a problem that is easy to understand and difficult to solve. As he has said, "there can be no veridical simulation of a belief system on a small scale [1973, p. 338]." Given all that must be represented as discrete facts and all the interrelations between these facts, a metaphysically adequate representation of a human belief system turns out to be enormous. However, a metaphysically adequate belief system for an instructional subject may be much simpler and smaller than a paranoid or a Cold Warrior belief system. As evidenced by the work of Goldberg and others (e.g., Kimball, 1973), the existing structure of instructional subject matter may lead to metaphysically adequate computer representations that lend themselves to relatively facile derivation of heuristics for the dynamics of instruction.

Overall, there appears to be useful progress on two fronts: (1) devising models of subject matter that, in turn, can model learners, and (2) modeling belief systems. Additionally, there are a few attempts to directly model human cognition in learning. Most of this activity stems from the early, influential development of EPAM (Elementary Perceiver and Memorizer) by Simon and Feigenbaum (e.g., 1964). EPAM is a computer program designed to act as a human subject in rote learning experiments. Its success has been substantial, and its behavior has been shown to be similar to that of human subjects in a variety of activities (e.g., Gregg and Simon, 1967; McLean and Gregg, 1967). EPAM might be used successfully to prescribe instruction for learners based on its "understanding" of their learning status, but an application of this sort has not been attempted. Hopefully, efforts of this sort based on the new models of human cognition are forthcoming.

Final Comment

It should be emphasized that attempts to devise adequate models of the learner are necessarily myopic. A truly adaptive instructional system must not only teach but learn. Such a system must embody models, procedures for hypothesis testing, and controls. The models provide formal representations of the subject matter, the learner, and their interaction. The procedures for hypotheses testing allow the system to draw conclusions concerning the behavioral characteristics of the learner. Finally, the controls enable the system to effect desired behavioral changes in the learner to accord with specified instructional objectives. A thorough discussion of these issues was recently prepared by Offir (1975).

CONCLUSION

Implicit in this review is the assumption that explicit representations of the learner should be applied in CAI. Instruction does not merely deposit information on blank slates. Students comprise complex, dynamic systems that are altered by instruction, and we need models for translating these systems to the effective procedures necessary for computer representations. Presumably, the better we explicate these student/systems, the better we can devise, modify, evaluate, and individualize instruction. Moreover, the approaches to instruction discussed by this paper use to advantage the power, speed, and accuracy of computers, and, in doing so, illustrate a unique and valuable capability of computers applied to instruction.

No general recommendations can be made concerning the approaches reviewed by this report. Models of memory support optimization of instruction, regression models promise wide applicability and the inclusion of supplementary information such as those of aptitude and personality characteristics, automaton models support direct investigation of the cognitive processes underlying problem solving by learners, and artificial intelligence techniques may provide the most complete representation of what the learner knows and does not know. Which of these approaches should be pursued will depend on the interests, goals, and capabilities of those investigating them.

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